Topological-Metrical Map Creation and Path Planning for Autonomous Indoor Mobile Robots

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Abstract. In this paper we present a framework to construct topological-metric 2D maps of indoor environments for autonomous mobile robot navigation. The topological part is represented by a bidirectional graph. Nodes in the graph represent one of the three kind of spaces characterized. Arcs represent a way of communication between them, usually a door. Spaces have been initially characterized in three classes: large or medium size rooms, and corridors. For each node in the graph a metrical map is constructed. Polylines structures have been used to represent data on metrical maps in order to incorporate more cognitive information. We propose that for each kind of room, a planning method should be used. Three path-planning methods were studied: classical visibility graphs, Voronoi diagrams and polygonal triangulation.

1. Introduction

A service robot can be used for many applications, including: cleaning & housekeeping, museum guidance, surveillance, etc. In order to achieve must of these tasks an autonomous mobile robot must be capable of construct and maintain maps of their environment while at the same time the robot need to be localized on it. Many techniques for this problem called "Simultaneous Localization and Mapping" or simply SLAM, have been proposed on recent years.

Researchers on the field have been proposed two major paradigms; by one side metrical map representations and topological maps on the other. For metric map representations such as grid-occupancy [1] or line-segments [2], powerful probabilistic methods have been developed within a single frame of reference. Many of these methods are accurate and reliable when doing online incremental localization

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within local neighborhoods. However, the complexity of metric maps often prohibits efficient planning and problem solving in large-scale indoor environments.

A topological map is a concise description of the large scale structure of the environment. It compactly describes the environment as a collection of places linked by paths. In order to have the topological representation, topological maps encode different information of the environment. For example in [82], a generalized Voronoi graph is used to encode salient features of the environment. On [54] a Delaunay Triangulation of the free space is used to generate topological map.

Topological and metrical methods for representing spatial knowledge have complementary strengths. To take advantage of their strengths some works have been proposed using hybrid (Topological-metric) maps, obtaining very good results [56]7.

However, for a service robot, it is important on one hand to understand the use and utility of each kind of area in order to better plan their path and actions; and on the other hand a service robot must be able to explain to an human how to arrive from one place to another, in a more natural human way. (i.e. Take first door and follow the corridor until ..., etc.). In order to achieve this task cognitive space representation should be as closer as possible to human conceptions. Moreover, understanding the uses and utility of each kind of space should bring a mobile robot the capacity to react or plan their actions in such kinds of specific environments. In other words a robot must be able to construct and maintain cognitive maps.

We proposed a cognitive map composed of a topological map of metric local space representations. Each local space defines a part of the environment that appears to enclose the robot: a room or a corridor. The advantage of such a map for a robot is that cumulative positional error is constrained to the local representation. Simpler localization methods will often suffice for the local environment as global metric consistency is not required.

The topological part is represented by a bidirectional graph, where nodes represent one of the three kinds of areas initially characterized. Arcs in the graph represent a way of communication between areas, usually a door. The areas initially characterized in three classes: large or medium size rooms, and corridors. For each node in the graph a metrical map is constructed. Polylines structures have been used to represent data on metrical maps in order to incorporate more cognitive information. As each kind of area has different characteristics, we propose to re-study path planning algorithms specifically for each kind of area in order to classified algorithms to be applied for a specific area. In this work, three path planning methods were studied initially: classical visibility graphs, Voronoi diagrams and polygonal triangulation.

This paper is organized as follow; section 2 refers to the way as each metric map is constructed with poly-lines structures by means of the discrete curve evolution method [128]. In section 3, specific areas are characterized and the topological part is constructed. Path planning methods and results for each area are shown in section 4, and finally in section 5 we express our conclusions and future work.

2 Discrete Curve Evolution Mapping

For metrical map robot creation internal geometric representation plays an important role. Typically, either, the planar location of laser range finder (LRF) is used directly as geometric representation, or simple features in the form of line segments or corner points are extracted [10, 11]. However, these simples and primitive geometric representations affect the overall performance of SLAM techniques.

Recently, polygonal curves or polylines representations have been used to deal with geometric mapping [8, 9]. This geometric representation is more compact and useful. Polyline representation captures more context than other features typically employed in scan matching approaches. Moreover, this internal representation fulfills requirements for the desired cognitlive and reasoning mapping.

In order to get the metric part of the approach proposed, initially, range data acquired by the LRF are stored as locations of reflection points in the Euclidean plane, represented as points. Thus, we obtain a sequence of scan points in the plane in a local coordinate system, the robot's heading aligned with the positive *y*-axis.

The order of the sequence of data reflects the order returned by the LRF. Nevertheless, in this sequence two consecutive points do not necessarily belong to the same object. The next step is to segment this sequence into polylines that represent visual parts of the scan. In this way, different objects in the scan sequence will not be represented by the same polyline. An object transition is said to be present wherever two consecutive points measured by the LRF are further apart than a given distance threshold.

For this segmentation, a simple heuristic is used: whenever the Euclidean distance of two consecutive points exceeds a given threshold we finish a polyline and start a new one. The obtained polylines represent boundaries of objects (Fig.1). Generally indoor environments are very structured, e.g. long walls, corridors, polygonal rooms, etc. We consider small polylines structures as noise, obstacles or moving objects no forming part of the map, talking about small the total length and/or the number of vertexes in the polyline structure.

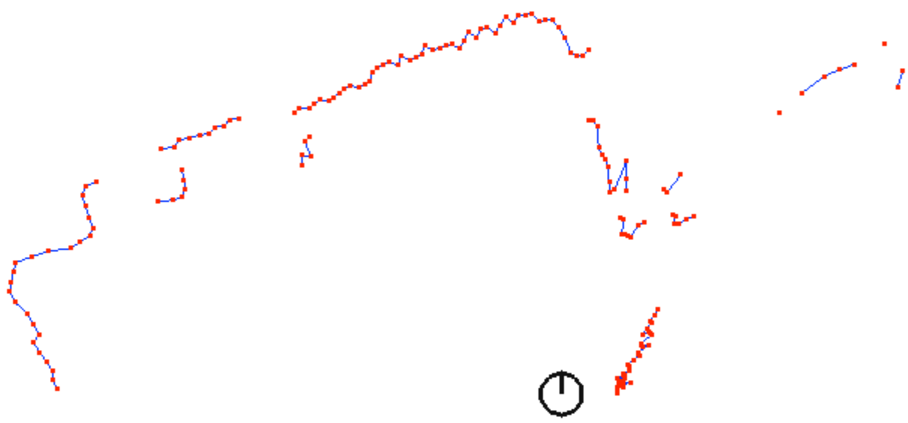

Fig. 1. Initially polyline map formed from segmented raw scan data, each polyline represent different objects. Smalls groups in length or number of vertex are considered noise or obstacles.

This part let us keep just the relevant polylines in the map reducing accumulative errors. Segmented polylines still contain all the information read form the LRF. Discrete Curve Evolution

We apply discrete curve evolution method (DCE), as proposed in [12], to reduce noise as well as to make the data compact without loosing valuable information. DCE is a context sensitive process that proceeds iteratively:

Let $\boldsymbol{P}$ be a polyline, we will denote the vertices of $\boldsymbol{P}$ with *vertices*($\boldsymbol{P}$). A discrete curve evolution produces a sequence of polylines $\boldsymbol{P} = \boldsymbol{P}_0, \ldots, \boldsymbol{P}_m$, such that each segment on the polyline has a cost function K greater than a given threshold. DCE can be summarized as follow:

```
For every evolution step i = 0,…, m − 1, a polyline P_{i+1}
is obtained after the vertices whose relevance measure
is: a) minimal and b) less than a given threshold, have
been deleted from P_i.
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To each vertex $\boldsymbol{v}$ in $\boldsymbol{P}_i$ is assigned a relevance measure $K(v, \boldsymbol{P}_i)$ that can be see as the cost of removing the given vertex in order to get a straight-line segment between its two neighbors.

In order to give a precise definition of the discrete curve evolution, we define $K_{min}(\boldsymbol{P}_i)$ to be the smallest value of the relevance measures for vertices of $\boldsymbol{P}_i$:

$$K_{min}(\boldsymbol{P}_i) = min\{K(\boldsymbol{u},\boldsymbol{P}_i) : \boldsymbol{u} \in vertices(\boldsymbol{P}_i)\} \quad \mathbf{(1)}$$

and the set $\boldsymbol{V}_{min}$ to contain the vertices whose relevance measure is minimal in $\boldsymbol{P}_i$:

$$\boldsymbol{V}_{min}\,(\mathbf{P}_i) = \{\mathbf{u} \in vertices(\mathbf{P}_i){:}\ K(\mathbf{u}, \mathbf{P}_i) = K_{min}(\mathbf{P}_i)\}, \text{ for } i = 0, \ldots, m - 1. \quad \mathbf{(2)}$$

For a given polyline $\boldsymbol{P}$ and a relevance measure K, we call a discrete curve evolution a process that produces a sequence of polylines $\boldsymbol{P} = \boldsymbol{P}_0,\ldots,\boldsymbol{P}_\mathrm{m}$ such that

$$vertices(\boldsymbol{P}_{i+1}) = vertices\ (\boldsymbol{P}_i) \,/\, \boldsymbol{V}_{min}(\boldsymbol{P}_i), \quad \mathbf{(3)}$$

The process of the discrete curve evolution is guaranteed to terminate, because it stops when the number of vertices are less than a given vertex threshold T_v or when there is no more relevance associated measures under the given relevance threshold T_r. On the other hand, if precedent conditions are not satisfied, in each evolution step, the number of vertices decreases by at least one.

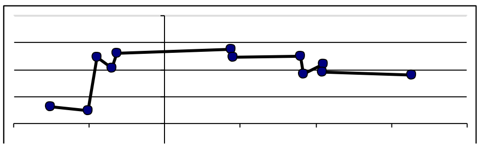
The key property of the evolution we used for our experiments is the order of the deletion determined by the relevance measure $K(\boldsymbol{v},\boldsymbol{P}_i)$ which depends on vertex $\boldsymbol{v}$ and its two neighbor vertices $\boldsymbol{u}$ and $\boldsymbol{w}$ in $\boldsymbol{P}_i$. It is given by the formula:

$$K(v,u,w) = K(\beta, l_1, l_2) = \beta \frac{l_1 l_2}{l_1 + l_2} \tag{4}$$

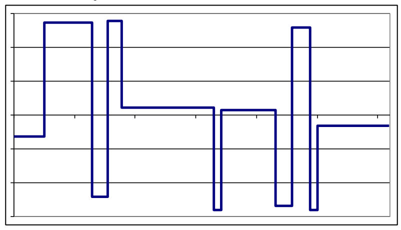
where β is the turn angle at vertex $\boldsymbol{v}$ in $\boldsymbol{P}_i$, l_1 is the length of segment $\boldsymbol{vu}$, and l_2 is the length of segment $\boldsymbol{vw}$ (Both lengths are normalized with respect to the total length of the polyline $\boldsymbol{P}_i$). Intuitively it reflects the shape contribution of vertex $\boldsymbol{v}$ in $\boldsymbol{P}_i$. The main property is the following:

The higher the value of $K(\boldsymbol{v},\boldsymbol{u},\boldsymbol{w})$, the larger is the contribution of arc $\boldsymbol{vu} \cup \boldsymbol{vw}$ to the shape of polyline $\boldsymbol{P}_i$. Relevance measure (4) has been defined in [12], where the tangential space is used to derive (Fig. 2).

Observe that this relevance measure is not a local property with respect to the polygon $\boldsymbol{P}$, although its computation is local in $\boldsymbol{P}_i$ for every vertex $\boldsymbol{v}$.



(a)



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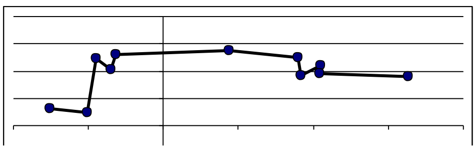

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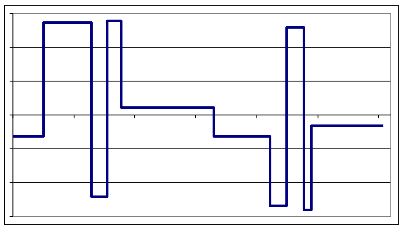

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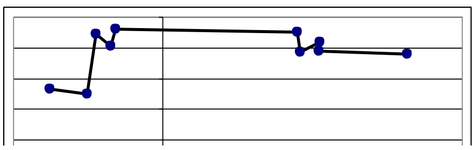

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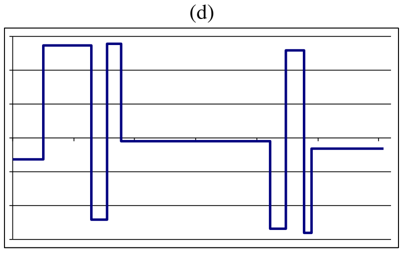

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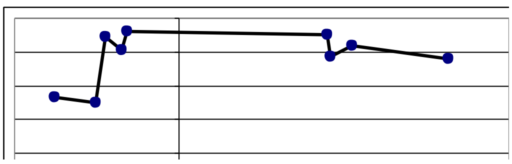
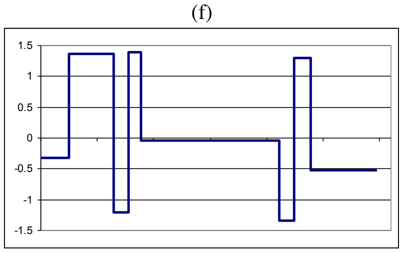
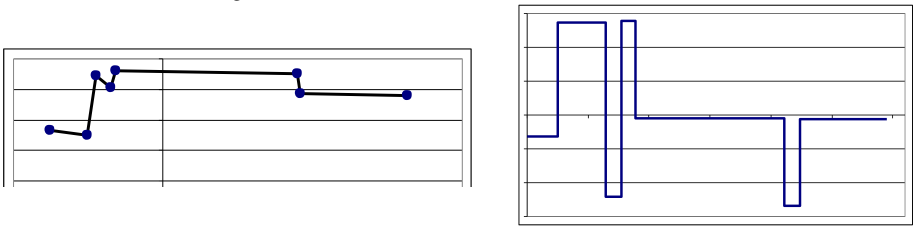




(g) (h)



(i) (j)

Fig. 2. Discrete curve evolution. In left images, it is shown different stages of the DCE method applied to one polyline structure. Images on the right side are the tangent space representation, used to compute the relevance measure K.

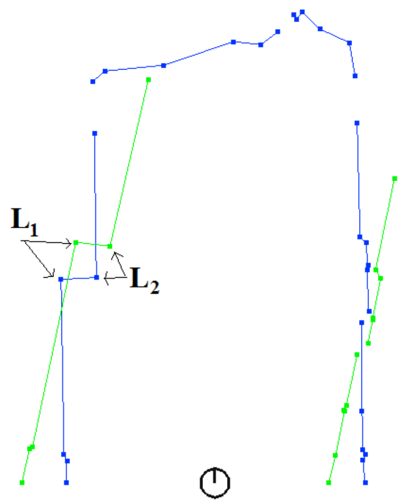


Fig. 3. Landmark selection based on relevance measure K. The length of adjacent segments and turn angles are used to get a similarity measure.

Finally, proceeding this way we obtain an ordered vector of polylines for each scan raw data.

To match polylines against the local metric map of the area, significant features, here also called landmarks are extracted, taking into account the higher relevance measures K, as computed in (4). As we can see in (Fig. 3), these vertexes are commonly the turning points on the polyline structure with most influence on its shape. These relevance measures K are the same computed on the final step of the DCE method.

Once this set features f_s have been selected for all the polylines in the current scan. We search the correspondence with a selected group of similar features in the map.

We select a subset f_g of visible features on the previous global map $G_{t\text{-}1}$ at the previous robot location $x_{t\text{-}1}$. These features are obtained in a similar way as for the single scans, determined by the relevance measure K over the polyline structure as described in [13].

The matching process uses as similarity measures: the relevance K for each selected landmark, as well as, the length l_1 and l_2 of the two adjacent segments (Fig. 4).

Landmarks near both edges of the field of view are commonly difficult to match, mainly because adjacent segments can be not completely perceive, so length of segments very different. Therefore, landmarks in polylines with the entire vertex inside the field of view have more weight for the matching process, than the landmarks inside polylines touching the field of view edges.

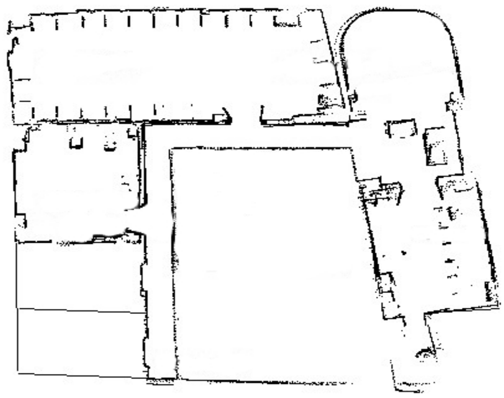


Fig. 4. Occupancy grid map of the environment used in this work

3 Area Characterization and Topological Map Construction

In order to obtain a local map for a specific area, it is considered in this work that each space to characterize has more or less a convex form, in other words the surface of the convex hull of the local area are very close to the surface of the area. If the difference is greater than a given threshold we try to segment this area into two or more pieces. Another consideration is that commonly a door can be easily extracted from polylines data, considering that there is a gap between polylines structures greater than a threshold, here 60 cm. In Fig. 5 it is show an occupancy grid of the environment used in this work.

We have defined initially three kinds of areas: large rooms, medium rooms and corridors. In Fig 6 are shown one example of each area. Basically, the difference between large and mediums rooms is defined only by a surface threshold, which in our case is 50 m^2. Corridors are determined using the size of their perpendicular sides, if the ratio of the sizes of the room is less than 1/3, and the smaller size is between certain measures, we select this area as a corridor.

The topological map is then created using the three classes of areas classified. Each node is then connected to the nodes by an arc for which there is a way of communication between them (i.e. a door). In Fig. 7 it is shown the resulting graph for a simple environment.

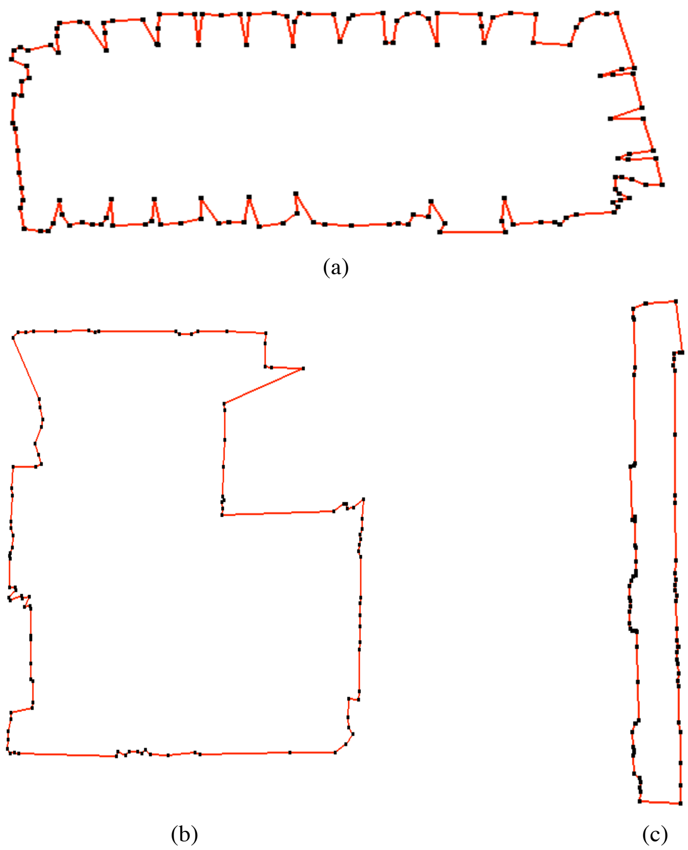


Fig. 5. Examples of areas classification: a) Large room (> 50m^2), computer center of IA dept at UV, (b) medium room (<50m^2) robotics classroom and (c) corridor.

4 Path Planning Study

At topological state, we solve path planning by means of a simple first in depth search. However, at each local metrical state a classical path planning method should be used. As each one of the characterized spaces have different uses and characteristics, it is important to evaluate different path planning methods in order to

get the ones with better results. Initially cognitive considerations as for example the use of each space are not considered, but it will be included in future studies.
In order to simplify the path planning labor, we are interested in methods that would bring us a predefined path for each surface, in other words, for each area we want to have a pre-computed partial solutions.

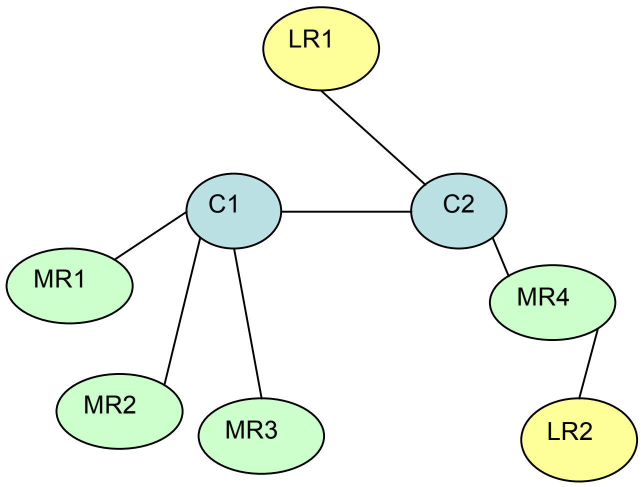


Fig. 6. Graph representing the topological extracted map: *LR* are Large rooms, *MR* are mediums rooms and *C* are corridors.

We have focused initially our study in three path-planning methods: Visibility graphs, Voronoi diagrams and polygonal triangulation. However, visibility graphs does not compute predefined paths, so it would be used at first to see if the destination point is visible from the initial point. If it is the case, as it will be most of the time, because, we have segmented the space in more o less convex shapes, we simply follow the line of sight between the given points. If is not the case, we search for the closer point of a preplanned path and we compute the trajectory to the closer point to the closer point, same on the preplanned path to the destination.

Many tests were made both on simulation areas and on real data. On Fig. 8 and 9 it is show the results for a medium and a large room with Voronoi diagram and polygonal triangulation methods.

	PATH		**Voronoi**			**Triangulation**		
	init. point (X1, Y1)	d (X2, Y2)	No. Segments	Distance	Complexity	No. Segments	Distance	Complexity
	1.000 0.345	3.345 4.234	26	5.754220	3.308904	67	73.168022	397.410240
No.	5.012 0.301	1.000 0.123	24	5.777176	4.787619	5	4.357837	21.746753

	3.589	3.431						
Points	2.567	0.354	10	5.819358	7.401335	24	34.665726	268.134192
	2.999	0.591						
	0.568	4.678	20	6.152320	3.630795	69	64.630630	279.185399
	0.391	5.431						
110	0.101	2.898	33	7.171617	3.490847	50	63.853653	258.275277

Table 1. Evaluation of paths for a medium room.

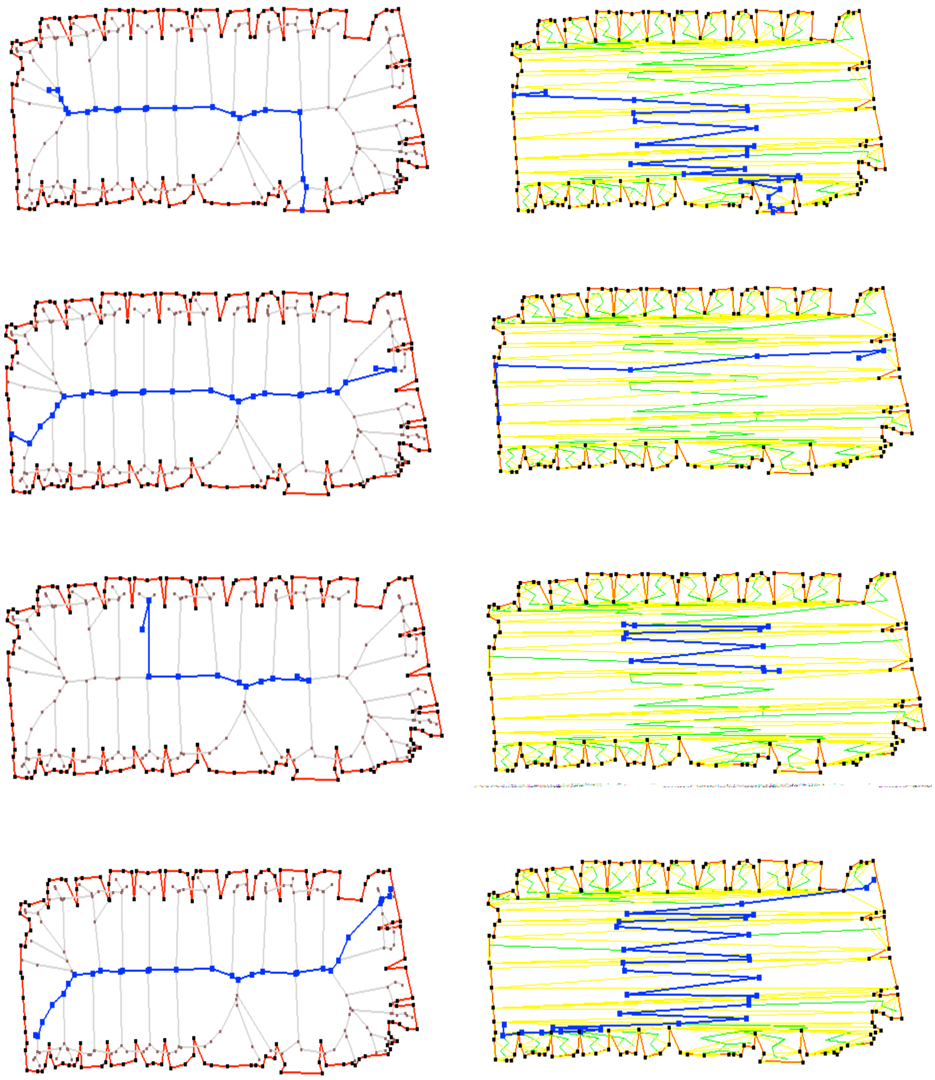


Fig. 7. Planned paths for a medium room: Left side Voronoi diagrams and right side polygonal triangulation.

	PATH			Voronoi			Triangulation	
	init. point (X1, Y1)	d (X2, Y2)	No. Segments	Distance	Complexity	No. Segments	Distance	Complexity
	1.254	9.450		11.13014			47.1181	69.3826
	3.258	0.155	22	7	4.798896	24	11	76
	11.769	0.232		13.56966			14.8218	9.15178
No.	3.404	1.678	26	0	7.734908	6	94	8
	4.211	8.999					21.9396	83.4062
Points	4.002	2.798	12	8.184609	5.843422	11	53	17
	12.589	0.557		13.92733			66.6289	90.9081
	4.880	1.101	31	2	4.261053	31	22	47
	9.450	10.829					6.93885	19.0797
145	0.288	0.742	13	0.000000	0.000000	10	3	23

Table 2. Evaluation of paths for a large room.

In order to evaluate the planned path for each method, we have proposed to compare them with the following characteristics: No of segments, total distance, and complexity of the path.

Complexity of the path is obtained by getting the surface of convex hull of the computed path, divided by the square of total distance. In tables, 1 and 2 are shown some results.

5 Conclusions and Future Work

In this work, we have proposed a method for construction of topological metric maps for mobile robots on indoor environments, which are closer to the human conception of spaces in uses and characteristics. A discrete curve evolution method has been used in order to simplify date acquired from the laser range finder, and to obtain structured features in the environment. We have proposed initially to consider three types of areas, large and mediums rooms, and corridors. With this classification, a topologic map is created which is solved in a simple way with a first in depth search. For each node in the graph the path planning in the metrical local map is solved by: 1) if the initial and destination points are visible we use the line of sigth, if not 2) we use the visibility graphs to get the closer point to a predefined path, computed with an specific method for each type of area. We have studied only predefined paths created with Voronoi diagrams and Polygonal triangulation. Polygonal triangulation have been show better results on simulation, however on real data is not very useful. The main problem with this method is that there is not a unique way to triangulate a polygon.

We propose as future work to evaluate more path planning methods as well to characterize more spaces. Information about the conditions of use of each area will be also incorporated.

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